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Predicting Limiting 'Free Sugar' Consumption Using an Integrated Model of Health Behavior

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Abstract

Excess intake of ‘free sugars’ is a key predictor of chronic disease, obesity, and dental ill health. Given the importance of determining modifiable predictors of free sugar-related dietary behaviors, we applied the integrated behavior change model to predict free sugar limiting behaviors. The model includes constructs representing ‘reasoned’ or deliberative processes that lead to action (e.g., social cognition constructs, intentions), and constructs representing ‘non-conscious’ or implicit processes (e.g., implicit attitudes, behavioral automaticity) as predictors of behavior. Undergraduate students (*N*=205) completed measures of autonomous and controlled motivation, the theory of planned behavior (TPB) measures of explicit attitude, subjective norms, perceived behavioral control (PBC), and intentions, past behavior, implicit attitude, and behavioral automaticity at an initial point in time, and free sugar limiting behavior and behavioral automaticity two weeks later. A Bayesian structural equation model indicated that explicit attitude, subjective norms, and PBC predicted behavior via intention. Autonomous motivation predicted behavior indirectly through all TPB variables, while controlled motivation predicted behavior only via subjective norms. Implicit attitudes and behavioral automaticity predicted behavior directly and independently. Past behavior predicted behavior directly and indirectly through behavioral automaticity and intentions, but not implicit attitudes. Current findings suggest pervasive effects of constructs representing both reasoned and non-conscious processes and signpost potential targets for behavioral interventions aimed at minimizing free sugar consumption.

Key Words: free sugar intake; theory of planned behavior; intentions; dual process; implicit attitudes; behavioral automaticity; habit; diet

Predicting Limiting 'Free Sugar' Consumption Using an Integrated Model of Health Behavior

There is growing evidence that a high intake of dietary sugars has deleterious effects on health and is linked to elevated risk of chronic disease (e.g., diabetes, cardiovascular disease, certain cancers) and conditions (e.g., overweight, obesity), and oral and dental ill health (Burt & Pai, 2001; Hu & Malik, 2010; Malik, Popkin, Bray, Després, & Hu, 2010). A major contributor to excess sugar intake is the consumption of '*free sugar*', which refers to sugars added to foods during preparation or naturally present in honey, syrup, or juice (World Health Organization, 2015). World Health Organization guidelines specify free sugars should account for no more than 10% of daily energy intake. However, national survey data suggests that the majority of people in developed countries fail to meet these guidelines (Australian Bureau of Statistics, 2016; The Office of Disease Prevention and Health Promotion, 2015).

Given the weight of evidence indicating the negative health effects of excess free sugar consumption, researchers have attempted to identify the correlates of consumption of high-sugar foods, particularly the theory-based psychological determinants of sugar consumption that are deemed modifiable through intervention. Much of the research has applied theories of social cognition that focus on determinants that reflect reasoned, deliberative processes to predict behavior (McEachan, Conner, Taylor, & Lawton, 2011). These theories assume that individuals form intentions to perform future behaviors based on their personal and social evaluation of the merits and detriments of performing the behavior in future, and their estimates of personal capacity to do so. While research based on these models have demonstrated efficacy in predicting dietary behaviors (Brown, Hagger, Morrissey, & Hamilton, 2018; McDermott et al., 2015), such models are limited in that they do not include determinants that reflect non-conscious processes. That is, processes which affect an individual's behavior without the need for excessive conscious processing and often beyond their awareness. Research has suggested that non-conscious processes have a pervasive effect on health behaviors (Hagger, 2016; Sheeran et al., 2016). The current study aims to extend this research by adopting an integrated model that incorporates multiple constructs that reflect both reasoned and non-conscious processes to identify the determinants of free sugar limiting behavior.

Integrated Theories of Behavior

Many of the leading theories adopted to predict health behaviors focus on constructs that represent reasoned processes that lead to behavior. A prototypical approach in this tradition is the theory of planned behavior (TPB; Ajzen, 1991). According to the model, individuals' intentions to perform a target behavior in future is a function of three belief-based constructs: *attitude*, the evaluation of the positive or negative consequences of the behavior, *subjective norms*, perceptions that significant others want them to perform the behavior, and *perceived behavioral control* (PBC), beliefs in their capacity to successfully perform the behavior. Consistent with reasoned action assumptions, intentions are proposed to mediate the effects of attitude, subjective norms, and PBC on behavior. Meta-analytic research has shown the TPB to account for a substantive proportion of the variance in health behavior across multiple studies (McEachan et al., 2011).

While the TPB provides an account of the determinants of action based on beliefs about of future behavior, relatively few studies have provided insight into the antecedents of these determinants. According to Ajzen (1991), individuals form beliefs on the basis of past experience and other dispositional and internal factors. One potential source of beliefs are the motivational orientations identified in self-determination theory (SDT; Ryan & Deci, 2000). Self-determination is a needs-based theory that identifies how motivational quality relates to behavior. According to the theory, individuals experiencing behaviors as autonomously motivated are likely to perceive their actions as emanating from, and consistent with, their authentic self, and they perform actions out of choice rather than due to externally reinforced contingencies. Individuals performing behaviors for autonomous reasons are more likely to persist with the behavior, and experience a sense of satisfaction and positive affect from doing so. Alternatively, individuals experience behaviors as controlled motivated perceive their actions as determined by externally-referenced contingencies such as rewards, punishments, or out of perceived obligation (e.g., to avoid shame or guilt). Although controlled reasons for acting are motivating, they lead to persistence only as long as the controlling contingencies are present and are not related to adaptive outcomes like satisfaction or positive affect.

Research has suggested that autonomous motives are a source of information for the formation of beliefs and intentions toward performing the behavior in future (Hagger & Chatzisarantis, 2009). Autonomous motivation is proposed to be related to positive attitudes, perceptions of control over future behaviors, and intentions to perform behaviors in future. In contrast, controlled motivation is related to subjective norms, as the latter often reflect beliefs about external social pressures to perform the behavior. The belief-based constructs and intentions are proposed to mediate effects of the SDT motives on behavior. These effects reflect an adaptive process in which individuals strategically align their beliefs with their motives so as to pursue behaviors consistent with their motives in future.

While integrated models of SDT and TPB constructs have provided some insight into the motivational factors that determine behavior, they do not provide a full account with small-to-medium sized effects on behavior (Hagger & Chatzisarantis, 2009). Researchers have therefore sought to augment these models with constructs that may account for additional variance in behavior. One approach has been to integrate constructs that reflect non-conscious processes that determine action into these models. Such constructs are derived from dual-process models of action such as the reflective-impulsive model (Strack & Deutsch, 2004). According to these models, behavioral enactment is a function of constructs that reflect reasoned processes, such as those from the TPB and SDT, and constructs that reflect non-conscious processes that affect individuals' behavior beyond their awareness. Such non-conscious processes are based on the premise that many frequently performed behaviors are enacted with little cognitive input. Rather, behavior is determined by representations and evaluations of the behavior that have been developed over time through consistent previous experience of the behavior covarying with behavioral evaluations. Such information, stored schematically, leads to automatic behavior initiation without the need for extensive reasoning and reflection.

Numerous constructs have been identified as representative of non-conscious determinants of behavior in dual process models. A prominent construct representing non-conscious processes is implicit attitudes, defined as the learned associations between target objects or actions and positive or negative evaluations (Greenwald & Banaji, 1995). Implicit attitudes are proposed to lead to rapid, efficient behavioral enactment on presentation of environmental cues or stimuli related to the attitude object or action that are stored alongside representations of the motor response (the behavior) in memory. The implicit attitude is automatically activated by the cue and the individual becomes predisposed to approach or avoid the attitude object or action (Chen & Bargh, 1999). Implicit attitudes are often measured using computer-controlled reaction time tasks such as the implicit association test (Greenwald, McGhee, & Schwartz, 1998) that present stimuli relating to the attitude object or action, and measure the speed at which individuals match the stimuli to evaluative attributes (often reflecting positive or negative evaluations). Meta-analyses have found that measures of implicit attitudes are effective in predicting behavior even when attitudes measured by explicit means, such as self-report items, have been taken into account (Greenwald, Poehlman, Uhlmann, & Banaji, 2009; Phipps, Hagger, & Hamilton, 2019). Such tests reflect independent effects of constructs representing reasoned and non-conscious behavioral determinants.

A further construct that may reflect non-conscious processes that lead to action is behavioral automaticity. Behavioral automaticity reflects the extent to which behaviors are experienced as ‘automatic’; that is, controlled by processes that are beyond an individual’s awareness. This is often measured through self-report measures such as the self-report behavioral automaticity index (Gardner, Abraham, Lally, & de Bruijn, 2012). Although individuals may be prone to making some errors when self-reporting the determinants of their behavior, it is assumed that individuals will generally have insight on the extent to which their behavior occurs through processes to which they have little conscious access. Automaticity is a key component of habits, and an indicator that an individual has performed the behavior frequently and in the presence of consistent contexts or cues that activate the behavior. Meta-analytic research has demonstrated that behavioral automaticity is a predictor of health behavior (Gardner, de Bruijn, & Lally, 2011).

It is important to note that constructs like implicit attitudes and behavioral automaticity, while related and often coincide (Hagger, 2019), are conceptually separate constructs and reflect different types of non-conscious processes. Despite this, little research examined the independent effects of implicit attitudes and automaticity on behavior. Furthermore, there is no research, that has explored their independent effects alongside constructs reflecting reasoned processes that determine behavior. The current research aims to fill this gap by using multiple measures representing non-conscious processes as predictors of limiting free sugar consumption alongside measures that represent reasoned processes.

Past Behavior Effects in the Model

Research applying social cognition and motivational models to the prediction of behavior has included past behavior as an additional determinant of behavior alongside constructs from the model. The rational for the inclusion of past behavior is that it should test the *sufficiency* of the model (c.f., Ajzen, 1991). Beyond this sufficiency hypothesis, effects of past behavior on subsequent behavior mediated by social cognition and motivational constructs may model previous decision making or, at least, the role previous behavior plays as a source of information in determining beliefs, motives, and intentions. In addition, residual effects of past behavior on subsequent behavior that are not mediated by reasoned pathways may provide important information on uncaptured behavioral determinants (Ouellette & Wood, 1998). These unmeasured constructs are likely to be those that relate to non-conscious determinants of behavior, which may mediate the past behavior-behavior relationship. For example, past behavior has been proposed as a ‘proxy’ for habitual influences on behavior. Although these effects have seldom been tested, van Bree et al. (2015) found preliminary support that self-reported habit mediated the effect of past behavior on subsequent behavior. In the current study, we proposed to extend these results by testing the extent to which residual effects of past behavior is mediated by constructs representing non-conscious processes; namely, implicit attitudes and behavioral automaticity. To the extent that these constructs mediate effects of past behavior on subsequent behavior we will have confirmation of the extent to which past behavior serves as a ‘proxy’ for multiple non-conscious determinants of this behavior.

A Bayesian Approach

In the current study, we adopted a Bayesian approach to test our proposed integrated model, which enabled us to integrate new observations with related previous research (Zyphur & Oswald, 2015). The Bayesian approach provides mean and variance estimates of current data that accounts for previous findings rather than estimating them in isolation as in more traditional analytic approaches. Consequently, the Bayesian structural equation model used to predict free sugar limiting behavior in the current study should result in more accurate parameter estimates than would be obtained using traditional regression or structural equation modelling techniques (for a detailed introduction to the use of Bayesian statistics in health psychology see Depaoli et al., 2017). In cases where the current observations are consistent with prior findings, Bayesian analysis will provide more precise estimates of the average model effects and their distributions. If a discrepancy is found between the prior research and new observations, the analysis will result in a highly variable distributions indicative of low precision.

The Current Study

The aim of the current study was to apply an integrated dual process model to identify the determinants of limiting free sugar consumption behavior and the processes involved. The model included multiple constructs representing both reasoned (social cognition beliefs, intentions, autonomous motivation) and non-conscious (implicit attitudes, behavioral automaticity) processes, and tested their simultaneous effects on prospectively-measured limiting of free sugar consumption. In the model, limiting free sugar consumption was proposed as a function of social cognitive and motivational constructs representing a reasoned process, whose effects on behavior were hypothesized to be mediated by intention, and constructs representing non-conscious processes, whose effects on behavior were hypothesized to be direct. Sufficiency of the model was tested by including past avoidance of free sugar consumption as an additional predictor of subsequent behavior alongside the model constructs. The extent to which past behavior 'models' non-conscious processes was also tested by examining the extent to which constructs representing non-conscious processes mediated residual effects of past behavior on subsequent behavior. The model was tested using a Bayesian analytic approach which enabled the specification of informative prior values for proposed effects in the model.

In terms of specific hypotheses (Table 1), attitude (H_{1a}) subjective norms (H_{1b}), and PBC (H_{1c}), from the TPB were expected to have direct non-zero effects on intentions to limit free sugar consumption, and intention was hypothesized to have a direct non-zero effect on prospectively measured free sugar limiting (H_{1d}). We also expected indirect non-zero effects of attitude (H_{2a}) subjective norms (H_{2b}), and PBC (H_{2c}) on free sugar limiting mediated by intention. Autonomous motivation was expected to have direct non-zero effects on the attitude (H_{3a}), subjective norm (H_{3b}), and PBC (H_{3c}) constructs from the TPB, while controlled motivation was expected to have direct non-zero effects on subjective norm (H_{3e}), but not attitude (H_{3d}) or PBC (H_{3f}). Autonomous (H_{4a}) and controlled motivation (H_{4c}) were expected to have indirect non-zero effects on free sugar limiting with attitude, subjective norms, PBC, and intentions (H_{4bd}) as multiple mediators. We expected a direct non-zero effect of behavioral automaticity on prospectively-measured limiting free sugar consumption. We also expected this effect to be mediated by prospectively-measured behavioral automaticity measured concurrently with the measure of limiting free sugar consumption (H_{5a}). Implicit attitudes were also hypothesized to have a direct non-zero effect on prospectively-measured free sugar limiting (H_{5b}). Finally, past behavior was expected to have a direct non-zero effect on prospectively-measured limiting of free sugar consumption (H_{6a}). We expected indirect non-zero effects of past behavior on limiting free sugar consumption mediated by the TPB constructs and intentions, behavioral automaticity, and implicit attitudes ($H_{6b\text{-}j}$).

Method

Study Design and Participants

The study adopted a two-occasion prospective survey design, with participants required to complete self-report measures of constructs from the proposed integrated model, past free sugar limiting behavior, and demographic variables at an initial data collection occasion (Time 1, T1), and follow-up measures of behavioral automaticity and free sugar limiting behavior at a second data collection occasion two weeks later (Time 2, T2). Participants were first year undergraduate students majoring in psychology recruited from an Australian university. Participants were eligible for inclusion in the study if they were part of the targeted undergraduate cohort, and completed a consent form agreeing to participate in the study and stating availability to be contacted at a later time for follow-up data collection. Two-hundred and thirty-three participants consented to participate in the study and completed study measures at T1. Twenty-eight participants dropped out of the study at T2 resulting in a final sample of 205 (M_{age} = 22.20, SD_{age}= 7.92; 46 males, 159 females). Eligible participants were granted course credit in return for their participation.

Implicit Association Test

Implicit attitudes were measured using a variation of the implicit association test, known as a single-target implicit association test (ST-IAT). The ST-IAT is a reaction time task in which participants match target stimuli related to the concept of interest, in this case sugar-related words, with attributes representing positive or negative valence. The ST-IAT used the same stimuli as administered by Hagger et al. (2017): 10 sugar related words as target stimuli, and 10 positive and 10 negative words as attribute stimuli (a list of stimulus words is available in Appendix B). For the purpose of streamlining IAT script creation and scoring, an IAT constructor program was made and used for creating the IAT and its scoring scripts. Scoring from this program was verified in R, and the program is available on the open science framework[1].

The ST-IAT was developed, administered, and analyzed consistent with published guidelines (Bluemke & Friese, 2008; Greenwald et al., 1998). Stimuli were presented on a personal computer using a standard screen and participants' responses to stimuli were made on a standard keyboard. Presentation of stimuli, timing, and data and error recording was controlled by the Inquisit experimental software. Participants first completed a practice block of stimuli-attribute trials to familiarize them with the task; followed by two 'test' blocks in which the free sugar words shared a response key with positive words, and two blocks in which the free sugar response key was paired with negative words. The order of positive or negative attribute/free sugar pairing blocks within the ST-IAT was counterbalanced. Errors were adjusted using the *D*-2*SD* scoring method (Greenwald, Nosek, & Banaji, 2003). Participants' implicit attitudes were expressed as a *D* score. Two versions of the *D* score were calculated: from the first set of positive and negative pairing blocks (Da), and from the second set of positive and negative pairing blocks (Db). The final *D* score was computed as the mean of Da and Db (Bluemke & Friese, 2008). Positive scores reflect a positive implicit attitude towards free sugar. Reliability for the ST-IAT is calculated by spearman adjusted correlation between D-scores for the Da and Db blocks.

Survey Measures

[1] The IAT constructor software can be accessed at(Phipps, 2019)

Participants completed self-report measures of theory constructs, free sugar limiting behavior, and demographic variables in an online survey administered by the Qualtrics software. Measures were preceded by a brief info-graphic relating to free sugar, followed by measures of demographic variables, and past behavior, autonomous and controlled motivation, social cognition constructs from the TPB, intentions, and behavioral automaticity. All participants completed measures in this order. Full survey measures are presented in Appendix A

Demographic variables. Participants were asked to self-report their age, gender, country of origin, height, and weight. Height and weight values were used to calculate participants' body mass index (BMI).

Behavioral Automaticity. Behavioral automaticity of limiting free sugar consumption was measured using the self-report behavioral automaticity index (Gardner et al., 2012; Verplanken & Orbell, 2003), with responses provided on 7-point scales (1 = *strongly disagree* and 7 = *strongly agree*).

Autonomous and Controlled Motivation. Autonomous and controlled motivations towards limiting free sugar were assessed with four items each. Scales comprised of the common stem "The reason I would limit free sugar in my daily diet is…", followed by statements as to why one may limit their free sugar consumption for autonomous (e.g. "because I personally believe it is the best thing for my health") or controlled (e.g. "because others would be upset with me if I did not") reasons. Responses were provided on 7-point scales (1 = *strongly disagree* and 7 = *strongly agree*)

Free Sugar Limiting Behavior. Participants' free sugar limiting behavior was assessed with a two-item measure addressing the frequency and extent of behavior over the previous two weeks (e.g. "Think about the past two weeks. How often did you limit free sugar in your daily diet?"), scored on a 7-point scale (1 = *never* and 7 = *Very often*). This measure was administered at both time points as to assess past and prospectively measured behavior.

Attitude. Participants' explicit attitude towards free sugar was assessed with four items preceded by a common stem: "For me, to limit free sugar in my daily diet in the next two weeks is…". Items were scored on 6-point sematic differential scales.

Subjective Norms. Subjective norms towards limiting free sugar intake were assessed by three items (e.g. "Most people who are important to me would want me to limit free sugar in my daily diet in the next two weeks"), with responses provided on 7-point scales (1 = *strongly disagree* and 7 = *strongly agree*).

Perceived Behavioral Control. Perceived behavioral control was assessed on four items (e.g., "It is mostly up to me whether I limit free sugar in my daily diet in the next two weeks"), with responses provided on 7-point scales (1 = *strongly disagree* and 7 = *strongly agree*).

Intentions. Participants' intentions to limit their free sugar intake over the following two weeks was assessed via four items (e.g., "I plan to limit free sugar intake in my daily diet in the next two weeks"), with responses provided on 7-point scales (1 = *strongly disagree* and 7 = *strongly agree*).

Procedure

Participants were asked to attend a laboratory appointment at T1. Upon arrival at the laboratory, participants were greeted by the researcher, shown to an experimental cubicle containing a desk, chair, and personal computer, provided with a study information sheet and asked to sign a consent form. Participants then completed the ST-IAT following instructions on the screen. Once they had completed the ST-IAT participants alerted the experimenter. The experimenter then directed them to the online questionnaire. On completion of the questionnaire, participants were thanked and reminded that they would be contacted two-weeks later and asked to participate in the second part of the study. At T2 participants were contacted via email with an invitation to complete follow up measures of behavioral automaticity and free sugar limiting behavior. Study procedures were approved by Griffith University's Human Research Ethics Committee.

Data Analysis

A Bayesian structural equation model specifying the hypothesized relations among constructs from the proposed integrated model was fitted in R using the Blavaan package (Makowski, 2018; Merkle & Rosseel, 2018; R Development Core Team, 2017). Where an identical path was tested, priors were sourced from (Hagger, Trost, Keech, Chan, & Hamilton, 2017). Otherwise, an objective prior was used (see Table 2). The model was run with three MCMC chains using the JAGS package (Depaoli, Clifton, & Cobb, 2016; Plummer, 2012). Starting values of MCMC chains were derived from maximum likelihood analysis. Should all Gelman-Rubin statistics indicate successful convergence (PSRF < 1.05; Gelman & Rubin, 1992), the necessary number of sample iterations to achieve accurate posterior estimates was specified by the Raftery-Lewis diagnostic (Raftery & Lewis, 1992). The final model was checked using the WAMBs checklist for quality and replicability (Depaoli & van de Schoot, 2017). Fit statistics are calculated using the posterior mean deviance method with the leave-one-out information criterion (Garnier-Villarreal & Jorgensen, 2019).

Model fit was evaluated using Bayesian adaptions of the root mean square error of approximation (BRMSEA), gamma hat (B $\hat{\gamma}$), and comparative fit index (BCFI). Results are presented as the mean and standard deviation of statistics between iterations. As the posterior predictive *p*-value (PPP) is the most common fit statistic for Bayesian modelling, PPP shall also be presented for the sake of comparison, with a PPP of .5 indicating optimum fit. However, the PPP is considered a poor indicator of fit, particularly in complex models (Cain & Zhang, 2018; Garnier-Villarreal & Jorgensen, 2019; Hoofs, van de Schoot, Jansen, & Kant, 2018; Levy, 2011), and should therefore be interpreted with caution.

We tested hypotheses using both Bayesian and frequentist analytic methods. Results are presented with 90% highest density intervals, as per recommendations for Bayesian analysis (Kruschke, 2014; Makowski, Ben-Shachar, & Lüdecke, 2019; McElreath, 2018). For comparability with the more common frequentist analysis, a maximum probability of effect (MPE) statistic is presented for each path. The MPE equals the proportion of iterations in which the standardized beta was in the same direction from zero (positive or negative) as the standardized posterior mean of all iterations. The MPE behaves similarly to a traditional *p* value, so that a MPE greater than .975 is conceptually equivalent to a *p* value of less than .05, while lower MPE values are synonymous with higher *p* value (Makowski, 2019); thus a MPE of .975 or higher is indicative of what would be considered a statistically significant effect when $\alpha = .05$ in an equivalent frequentist analysis.

To allow for a strict Bayesian interpretation, the log adjusted Savage-Dickey Bayes Factor (logBF) is also reported for all direct parameter estimates. While the logBF statistic does not give a difference from zero figure, it provides a useful comparison of the null hypothesis, prior distributions, and current observations for each proposed effect in the model (Wagenmakers, Lodewyckx, Kuriyal, & Grasman, 2010). Should the current observations increase the likelihood the true mean for an effect is not zero as compared to the prior, the logBF will be positive, while a negative logBF indicates current data increases confidence the true parameter mean is zero as compared to the prior.

Results

Preliminary Analyses

Independent samples *t*-tests found that participants that dropped out of the study after T1 did not differ from participants included in the final sample at T2 on age ($t(230) = .97$, $p = .333$), height ($t(230) = .1.25$, $p = .213$), weight ($t(230) = .27$, $p = .787$), and gender ($\chi^2(1) = 2.87$, $p = .090$). Regarding behavioral and psychological variables, there was no significant difference between those who provided data at both time-points and those who did not (Wilk's Lambda = .94, $F(9, 220) = 1.61$, $p = .113$). Survey measures of model constructs exhibited acceptable reliability ($\alpha > .70$). The ST-IAT showed suboptimal reliability (ST-IAT $r = .32$ adjusted, $p = .006$). There was no effect of the order of blocks within the ST-IAT ($t(203) = .29$, $p = .775$). Complete reliability statistics and zero-order intercorrelations among study constructs are available in Appendix C (supplementary materials).

Bayesian Structural Equation Model

Model Fit. The model converged successfully after 10,000 post-burnin iterations (all PSRF values > 1.05). The Gelman-Rubin statistic indicated a further 7088 iterations were needed for accurate posterior estimates. After 17088 iterations effective sample sizes for all estimates exceeded 200. The WAMBs checklist procedures also signaled the model had good convergence, as well as a sufficient number of iterations and a low risk of bias (see Appendix D). BRMSEA ($M = .061$, $SD = .001$), B $\hat{\gamma}$ ($M = .907$, $SD = .004$), and BCFI ($M = .917$, $SD = .004$) indicate good fit of the model with the data (Garnier-Villarreal & Jorgensen, 2019). In contrast, the PPP indicated poor fit (PPP = .000). All but one factor loading exceeded the .5 cutoff, except for one controlled-motivation item.

Testing Model Hypotheses. Overall the model predicted 56.7% of sugar limiting intentions and 44.7% of sugar limiting behavior. The final model with standardized path estimates is displayed in Figure 1. Posterior means, standard deviations, highest density intervals, and log adjusted Bayes factors for all paths are presented in Table 2. We found direct non-zero effects of attitudes (H_{1a}), subjective norms (H_{1b}), and PBC (H_{1c}) on intentions, and a direct non-zero effect of intentions on free sugar limiting (H_{1d}). Bayes factors for the attitude–intention, the PBC–intention, and the intention–behavior relationships supported a modest increase in confidence of non-zero effects. The logBF for the subjective norms–intention relationship was negative, indicating a mild decrease in confidence of a non-zero effect. In addition, we found positive non-zero indirect effects of attitudes (H_{2a}), subjective norms (H_{2b}), and PBC (H_{2c}) on behavior via intention.

Consistent with hypotheses, autonomous motivation had positive and direct non-zero effects on attitude (H_{3a}), subjective norms (H_{3b}), and PBC (H_{3c}). As hypothesized, controlled motivation had a positive non-zero effect on subjective norms (H_{3e}). Positive logBF values for these relationships supported a moderate increase in confidence of a non-zero effect. Effects of controlled motivation on attitude (H_{3d}) and PBC (H_{3f}) were small, with MPE values below the .975 significance threshold. Negative logBF values for the controlled motivation–explicit attitude and controlled motivation–PBC relationships indicate a modest increase in confidence that the true posterior means are zero. Indirect effects of autonomous motivation on intentions ($H4_a$) and behavior ($H4_b$) were found through all social cognitive constructs. There was also a non-zero positive effect of controlled motivation on intentions ($H4_c$) and behavior ($H4_d$) through subjective norms, but with a substantially lower effect size than autonomous motivation. Consistent with hypotheses, behavioral automaticity (H_{5a}) and implicit attitudes (H_{5b}) had direct non-zero effects on behavior. Positive logBFs for the prediction of behavior by automaticity and implicit attitudes support a mild-modest increase in confidence that the true parameter means for these relationships are non-zero.

In line with our hypotheses, we found direct non-zero effects of past behavior on free sugar limiting (H_{6a}), autonomous motivation (H_{6b}), controlled motivation (H_{6c}), attitude (H_{6d}), and PBC (H_{6f}). However, contrary to predictions, past behavior had a non-zero and negative effect on subjective norms (H_{6e}). As predicted, we found a positive non-zero effect of past behavior on behavioral automaticity (H_{6h}). However, effects of past behavior on implicit attitudes (H_{6i}) and intentions (H_{6g}) were zero in contrast to our hypotheses. In line with findings from the inspection of MPEs, log Bayes factors were positive for all effects except for the effects of past behavior on implicit attitudes and intentions. We also found positive non-zero indirect effects of past behavior on free sugar limiting behavior via the TPB constructs, intentions, autonomous motivation, and behavioral automaticity (H_{6j}). The expected indirect non-zero effect of past behavior on free sugar limiting through implicit attitudes was not found. Finally, we found a positive non-zero total effect of past behavior on behavior.

Discussion

This prospective study aimed to identify the determinants of free sugar limiting behavior using an integrated dual process model. The model incorporated theory-based constructs representing reasoned and non-conscious processes as determinants of prospectively-measured behavior. Results showed that free sugar limiting behavior was predicted by constructs representing reasoned processes (attitudes, subjective norms, and perceived behavioral control, and intentions), and by both constructs representing non-conscious processes, behavioral automaticity and implicit attitudes.

Current findings are consistent with, and extend, previous research integrating constructs from social cognition and motivational theories in health behavior domains. Specifically, current research supported indirect effects of autonomous motivation from self-determination theory on intentions and behavior mediated by the attitudes, subjective norms, and PBC from the theory of planned behavior (Allom et al., 2018; Brown et al., 2018; Hagger & Chatzisarantis, 2009; Hagger et al., 2017; Hamilton, Kirkpatrick, Rebar, & Hagger, 2017). Controlled motivation also predicted behavior mediated by subjective norms. These findings are congruent with the tenets of self-determination theory (Deci & Ryan, 2000; Ryan & Deci, 2000) and proposals of integrated models. Individuals who expect to experience behaviors like limiting free sugar intake to be congruent with self-endorsed reasons and goals are more likely to align their beliefs with their motives. Controlled motivation was also indirectly related to behavior through subjective norms. This means that individuals who feel that limiting free sugar intake is something they feel pressured to do are more likely to view significant others as endorsing the behavior in future, which also determines intention. Taken together, the constructs representing the reasoned processes had pervasive effects on limiting free sugar consumption, and the indirect effects of autonomous motives through beliefs and intentions provides some evidence of a potential process.

Consistent with dual process theories (Krishna & Strack, 2017; Perugini, 2005; Perugini, Richetin, & Zogmaister, 2010; Strack & Deutsch, 2004; Wilson, Lindsey, & Schooler, 2000), constructs that represent non-conscious processes in the enactment of behavior were direct predictors of free sugar limiting. Specifically, implicit attitudes and behavioral automaticity predicted behavior with effect sizes that were similar in size to the effect of intention on behavior. These findings suggest that constructs representing non-conscious processes were at least as strong as those representing reasoned processes when it comes to predicting free sugar limiting behavior. The high availability of free sugar in the average diet means that individuals' are likely to have had repeated experiences of sugar consumption. Those experiences are also likely to have coincided with positive evaluations, given that consuming sugar is highly rewarding. These experiences are likely to have resulted in strong implicit attitudes towards sugar, which will negatively affect future actions aimed at limiting sugar consumption. In contrast, repeated experiences of limiting free sugar intake in the presence of stable contexts or cues may drive the development of a habit to limit sugar intake. This will result in individuals tending to enact their sugar limiting behavior non-consciously and independent of reasoned processing, a process captured in the present study by the direct effect of behavioral automaticity on behavior independent of intentions (Hagger, 2020).

In terms of broader theory, current findings mirror results of tests of integrated models that incorporate constructs representing reasoned and non-conscious processes in other behaviors (Allom et al., 2018; Brown, Hagger, & Hamilton, 2017; Caudwell & Hagger, 2014; Conroy, Hyde, Doerksen, & Ribeiro, 2010; Hamilton et al., 2017; Keatley, Clarke, & Hagger, 2013; Mullan et al., 2016; Tappe & Glanz, 2013). The current study extends this research by incorporating multiple constructs representing non-conscious processes, namely implicit attitudes and behavioral automaticity, and demonstrate their independent direct effects on behavior. That each has an independent effect is a unique finding in the present study and provides further corroboration that constructs representing the non-conscious process are conceptually distinct and have predictive validity. That intentions, implicit attitudes, and behavioral automaticity account for relatively equal proportions of the variance in limiting free sugar consumption indicates that this behavior, for some people, is not fully determined by intentions, which represent the reasoned deliberative processes. The implicit constructs represent multiple non-conscious influences on the current study: implicit attitudes toward sugar represent how positive evaluations of sugar may dampen individuals sugar limiting behavior, while behavioral automaticity represents the extent to which limiting free sugar consumption has become habitual. Given the relative parity in effect sizes for constructs representing the reasoned and non-conscious process on limiting free sugar consumption, an important consideration for future research is to establish the conditions in which each of the constructs ‘wins out’ in determining behavior (Hagger et al., 2017). Such research would provide a basis for tailoring interventions that target change in the relevant constructs and concomitant change in behavior.

Previous research has highlighted the importance of including past behavior as a behavioral predictor to test the sufficiency of social cognition theories (Ajzen, 1991; Albarracin, Johnson, Fishbein, & Muellerleile, 2001; Hagger, Chan, Protogerou, & Chatzisarantis, 2016; Hagger, Polet, & Lintunen, 2018; Ouellette & Wood, 1998). Past behavior is proposed to serve as a ‘proxy’ for habits, unmeasured behavioral determinants, and previous decision making. Consistent with previous analyses, past behavior effects on free sugar limiting in the present study was mediated by the social cognition and motivational constructs. This corroborates conceptual proposals that belief-mediated past behavior effects represent previous decision making and formation of beliefs on the basis of previous experience (Ajzen, 2002). There were, of course, substantive residual effects of past behavior, consistent with previous observations (Ouellette & Wood, 1998; Albarracín et al., 2001; Hagger et al., 2016; Hagger et al., 2018). Identifying the mediators of the residual effects may shed light on the processes reflected by past behavior effects. In the current study, behavioral automaticity was a candidate mediator, suggesting that, at least in part, past behavior reflects habits consistent with previous research (Hamilton et al., 2017; van Bree et al., 2015). This mediated effect is likely an indicator of the importance of repetition to habit formation. However, in contrast to our hypothesis, the effect of past behavior on limiting free sugar consumption was not mediated by implicit attitudes. Such a pattern further demonstrates that implicit attitudes reflect independent non-conscious processes. It seems that such beliefs may not be directly related to immediate previous experience. It is possible that the development of implicit attitudes occurs over a longer period of time in line with early theories of implicit attitudes (Sloman, 1996). Thus, behavior in the recent past, such as in the past two weeks in the present study, may not adequately capture such a long-term process.

Strengths, Limitations, and Future Directions

The current study has numerous strengths including: (i) a focus on the determinants of limiting free sugar consumption, a behavior that has potential to yield substantive health benefits and address a priority public health target; (ii) adoption of a unique integrated dual process model that incorporates multiple measures representing reasoned and non-conscious processes proposed to determine action; and (iii) adoption of a prospective design, and use of rigorous methods and data analytic techniques including a Bayesian approach to test model effects with informative priors from previous research. However, some limitations should be acknowledged. First, the current study was conducted in a student sample, while such research has bone-fide value to the student population and provides a means to test the predictive validity of theories, it is important to acknowledge that current findings should not be generalized to the broader population. Future studies should consider replication of the current model in randomly-selected stratified samples from the general population. Second, the correlational nature of the current research precludes any implications of causation. Thus, while current findings may implicate non-conscious processes as determinants of free sugar limiting behavior, such a hypothesis still requires further investigation in the form of longitudinal and experimental studies. Further, the self-reported nature of behavior in the current research means any implication that reasoned and non-conscious processes predict true free sugar limiting behavior should be viewed with a degree of caution. Subsequent research may seek to confirm the current findings with objective measures of behavior. It is also important to note the ST-IAT used to measure free sugar implicit attitudes displayed sub-optimal reliability. While a potential concern, these findings are consistent with those of other studies employing the ST-IAT; the task tends to have lower reliability than the traditional IAT (Bar-Anan & Nosek, 2014). Such poor reliability may lead to smaller effect sizes for parameter estimates, and should be interpreted accordingly.

Finally, while we found non-zero indirect effects of autonomous motivation on behavior and beliefs on behavior, the effect sizes were small. Similarly, despite a medium-sized zero-order correlation between intentions and behavior, the direct effect of intentions on behavior in the current study, was relatively modest. In contrast, past behavior had the largest effects on limiting free sugar consumption. A positive interpretation of these findings is that current data point to the sufficiency of the model in accounting for unique variance. However, the modest variance accounted for may suggest that the model provides only a limited account of the determinants of free sugar limiting behavior. One possibility is that measurement imprecision may be responsible for the small effects, for example implicit attitudes reflect general attitudes towards the behavior and, therefore, lack correspondence with the specific behavior. An alternative is that the current study did not adequately capture the full gamete of behavioral determinants, such as environmental effects (e.g., availability, proximity of sugar-rich foods)(Zhang, Wong, Zhang, Hamilton, & Hagger, 2019), self-control (Hagger, Gucciardi, Turrell, & Hamilton, 2019; Hagger, Hankonen, et al., 2019), response inhibition (Allom et al., 2016), and personality and individual differences (Vo & Bogg, 2015) all of which have been shown to be related to dietary behaviors. Future research may consider incorporating these constructs as determinants within the integrated model.

Conclusions

The aim of the current study was to investigate the predictors of free sugar limiting behavior using an integrated dual process model uniquely featuring multiple constructs that represent non-conscious processes. Current findings provide further support for using integrated models of behavior to test key predictors of health behavior. Further, current findings indicate that, despite their conceptual similarities, the non-conscious processes of implicit attitudes and behavioral automaticity predicted behavior independently. Taken in concert with the relative parity in effect sizes of implicit attitudes, behavioral automaticity, and intentions on behavior, these findings indicate the need for further research on the situations in which each of these determinants affect behavior. Further, the parity in the effect sizes may indicate a potentially valuable area for novel or combined interventions: strategies targeting conscious beliefs alongside implicit beliefs and habit change could offer improved outcomes on current programs. For example, researchers should consider strategies that foster strong habits and simultaneous positive evaluations, such as experiencing success and positive feedback in performing behaviors like free sugar limiting in consistent contexts and in the presence of consistent cues (Gardner, Rebar, & Lally, 2020; Hagger, 2020). Future research should seek to expand upon these findings using objective measures of behavior, generalizable samples, and longitudinal and experimental designs.

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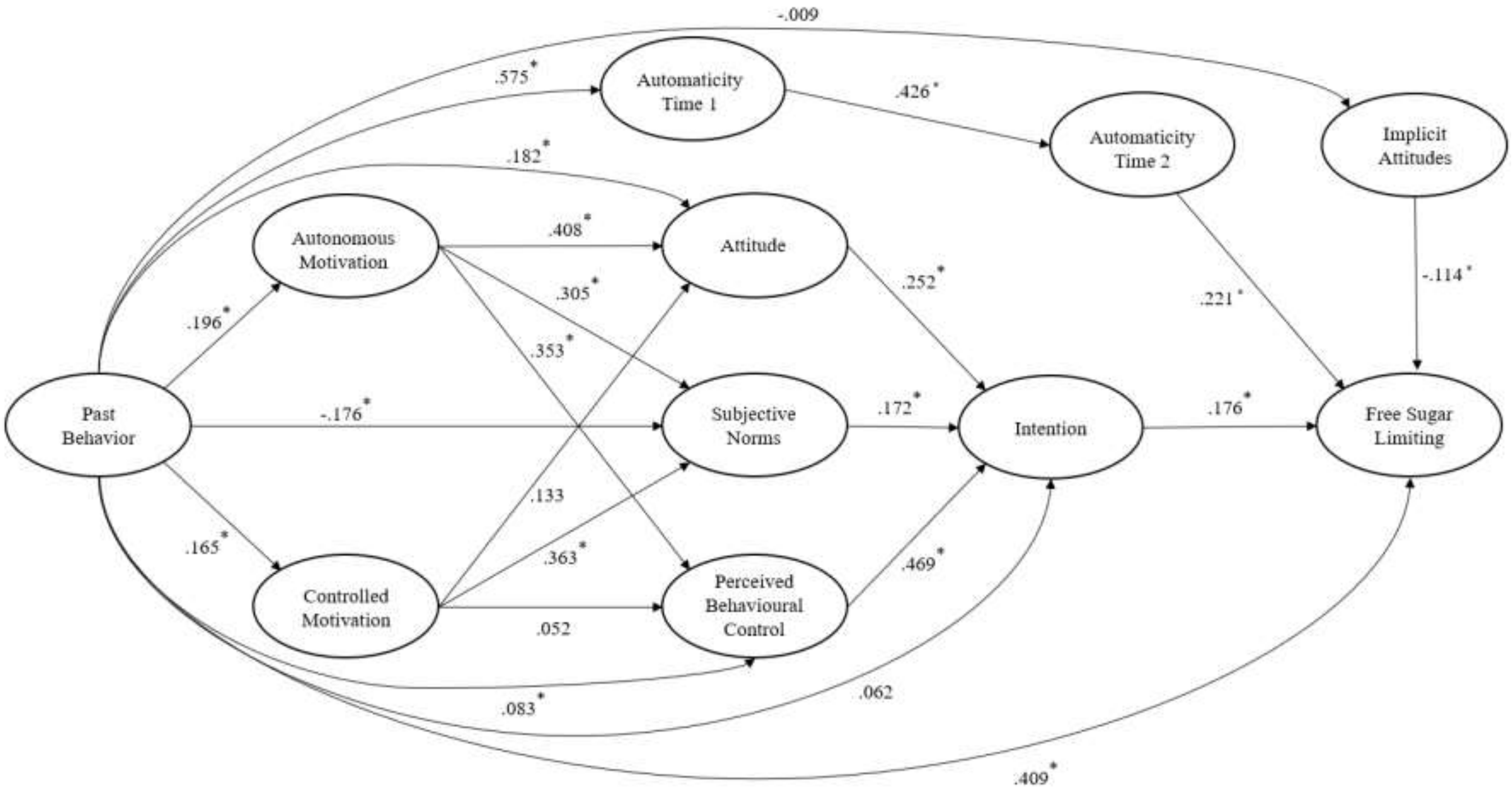

Figure 1. The proposed structural model including standardized beta of posterior means. * indicates an MPE of standardized beta above 97.5%, conceptually equivalent to $p < .05$ in frequentist terms.

Table 1

Summary of hypothesized direct and indirect effects in an integrated model of free sugar limiting

Hypothesis	Dependent Variable	Independent Variable	Mediator(s)	Prediction
H_1: Social Cognitive Constructs → Intention/Behavior				
H_{1a}	Attitude	Intention	-	Effect (+)
H_{1b}	Subjective Norms	Intention	-	Effect (+)
H_{1c}	PBC	Intention	-	Effect (+)
H_{1d}	Intention	Free Sugar Limiting	-	Effect (+)
H_2: Social Cognitive Constructs → Intentions → Behavior				
H_{2a}	Attitude	Free Sugar Limiting	Intention	Effect (+)
H_{2b}	Subjective Norms	Free Sugar Limiting	Intention	Effect (+)
H_{2c}	PBC	Free Sugar Limiting	Intention	Effect (+)
H_3: Self Determination Theory Motivation → Social Cognitive Constructs				
H_{3a}	Autonomous Motivation	Attitude	-	Effect (+)
H_{3b}	Autonomous Motivation	Subjective Norms	-	Effect (+)
H_{3c}	Autonomous Motivation	PBC	-	Effect (+)
H_{3d}	Controlled Motivation	Attitude	-	Effect (+)
H_{3e}	Controlled Motivation	Subjective Norms	-	Effect (+)
H_{3f}	Controlled Motivation	PBC	-	Effect (+)
H_4: Self Determination Theory Motivation → Social Cognitive Constructs → Intentions → Behavior				
H_{4a}	Autonomous Motivation	Free Sugar Limiting	Attitude Subjective Norms PBC Intention	Effect (+)
H_{4b}	Autonomous Motivation	Intention	Attitude Subjective Norms PBC	Effect (+)
H_{4c}	Controlled Motivation	Free Sugar Limiting	Attitude Subjective Norms PBC Intention	Effect (+)
H_{4d}	Controlled Motivation	Intention	Attitude Subjective Norms PBC	Effect (+)
H_5: Non-Conscious Constructs → Behavior				
H_{5a}	Automaticity (T1)	Free Sugar Limiting	Automaticity (T2)	Effect (+)
H_{5b}	Implicit Attitudes	Free Sugar Limiting	-	Effect (-)
H_6: Past Behavior → All Constructs				
H_{6a}	Past Behavior	Free Sugar Limiting	-	Effect (+)
H_{6b}	Past Behavior	Autonomous Motivation	-	Effect (+)
H_{6c}	Past Behavior	Controlled Motivation	-	Effect (+)
H_{6d}	Past Behavior	Attitude	-	Effect (+)
H_{6e}	Past Behavior	Subjective Norms	-	Effect (+)
H_{6f}	Past Behavior	PBC	-	Effect (+)
H_{6g}	Past Behavior	Intention	-	Effect (+)
H_{6h}	Past Behavior	Automaticity (T1)	-	Effect (+)
H_{6i}	Past Behavior	Implicit Attitudes	-	Effect (-)
H_{6j}	Past Behavior	Free Sugar Limiting	Autonomous Motivation Controlled Motivation Attitude Subjective Norms PBC Intention Automaticity Implicit Attitude	Effect (+)

Table 2

Prior Distributions for All Predicted Paths for Predicting Free Sugar Limiting Behavior

	Prior Distribution				
Path	Type	Shape	Mean	Precision	*df*
Autonomous Motivation → Attitude	Informed	*t*-distribution	.494	.886	89
Autonomous Motivation → PBC	Informed	*t*-distribution	.210	1.206	89
Autonomous Motivation → Subjective Norms	Informed	*t*-distribution	.132	.592	89
Controlled Motivation → Attitude	Informed	*t*-distribution	.006	.918	89
Controlled Motivation → Subjective Norms	Informed	*t*-distribution	.314	1.089	89
Controlled Motivation → PBC	Informed	*t*-distribution	-.270	.500	89
Attitude → Intention	Informed	*t*-distribution	.252	.935	89
Subjective Norms → Intention	Informed	*t*-distribution	.260	1.313	89
PBC → Intention	Informed	*t*-distribution	.055	.935	89
Intentions → Sugar Limiting	Informed	*t*-distribution	.288	1.313	89
Automaticity (T1) →Automaticity (T2)	Objective	Normal	.000	.001	-
Automaticity (T2) → Free Sugar Limiting	Objective	Normal	.000	.001	-
Implicit Attitudes → Free Sugar Limiting	Informed	*t*-distribution	-.512	1.538	89
Past Behavior → Free Sugar Limiting	Informed	*t*-distribution	.608	2.029	89
Past Behavior → Autonomous Motivation	Informed	*t*-distribution	.333	.575	89
Past Behavior → Controlled Motivation	Informed	*t*-distribution	.170	.103	89
Past Behavior → PBC	Informed	*t*-distribution	.311	.434	89
Past Behavior → Subjective Norms	Informed	*t*-distribution	-.017	.343	89
Past Behavior → Attitude	Informed	*t*-distribution	.155	.953	89
Past Behavior → Intention	Informed	*t*-distribution	.102	.689	89
Past Behavior → Implicit Attitude	Informed	*t*-distribution	-.088	.451	89
Past Behavior → Automaticity (T1)	Objective	Normal	.000	.001	-

Note. Objective distributions are not truly objective; however, the specified precision is extremely low and any effect of these priors should be near non-existent. SDT refers to the Self-Determination Theory constructs of Controlled and Autonomous Motivation. TPB refers to the Theory of Planned Behavior constructs of attitude, subjective norms, perceived behavioral control, and intention.

Table 3

Unstandardized and Standardized Posterior Parameter Estimates with Highest Posterior Density and Hypotheses Testing Statistics

Path	Post. Mean	Post. SD	.050 HPD	.950 HPD	β	MPE	logBF
Direct Effects							
Autonomous Motivation → Attitude	.558*	.143	.329	.804	.408	1.000	5.603
Autonomous Motivation → PBC	.184*	.049	.105	.264	.353	1.000	4.037
Autonomous Motivation → Subjective Norms	.549*	.194	.242	.868	.305	.999	2.367
Controlled Motivation → Attitude	.099	.064	-.006	.205	.133	.932	-1.556
Controlled Motivation → PBC	.015	.021	-.019	.049	.052	.768	-3.648
Controlled Motivation → Subjective Norms	.355*	.104	.187	.524	.363	1.000	3.549
Attitude → Intention	.285*	.119	.087	.474	.252	.992	0.689
Subjective Norms → Intention	.148*	.064	.041	.250	.172	.991	-0.155
PBC → Intention	1.391*	.280	.916	1.838	.469	1.000	11.033
Intention → Behavior	.254*	.104	.081	.425	.176	.994	0.452
Automaticity (T1) → Automaticity (T2)	.451*	.073	.328	.570	.426	1.000	14.167
Automaticity (T2) → Behavior	.218*	.066	.109	.325	.221	.999	0.452
Implicit Attitudes → Behavior	-.467*	.226	-.844	-.099	-.114	.981	0.455
Direct Effects: Past Behavior							
Past Behavior → Autonomous Motivation	.196*	.034	.137	.251	.494	1.000	13.001
Past Behavior → Controlled Motivation	.165*	.064	.061	.270	.226	.997	0.545
Past Behavior → Attitude	.182*	.047	.106	.260	.335	1.000	4.393
Past Behavior → Subjective Norms	-.176*	.069	-.289	-.063	-.246	.995	0.553
Past Behavior → PBC	.083*	.018	.054	.112	.402	1.000	6.795
Past Behavior → Intention	.061	.050	-.021	.142	.099	.890	-2.264
Past Behavior → Automaticity (T1)	.575*	.058	.482	.671	.669	1.000	44.766
Past Behavior → Implicit Attitudes	-.009	.017	-.036	.018	-.039	.699	-3.972
Past Behavior → Behavior	.409*	.071	.293	.527	.454	1.000	13.451
Covariances							
Behavior Automaticity ↔ Implicit Attitudes	.045	.042	-.024	.111	.079	.863	-
Autonomous Motivation ↔ Controlled Motivation	.196*	.073	.070	.309	.255	.999	-
Attitude ↔ Subjective Norm	.182*	.089	.039	.330	.242	.990	-
Attitude ↔ PBC	.029	.021	-.003	.065	.155	.939	-
Subjective Norms ↔ PBC	-.043	.029	-.089	.005	-.145	.934	-
Indirect and Total Effects							
Autonomous Motivation → Attitude → Intention → Behavior	.040*	.027	-.051	.260	.018	.985	-
Autonomous Motivation →Subjective Norms → Intention → Behavior	.020*	.015	.029	.155	.009	.998	-
Autonomous Motivation → PBC → Intention → Behavior	.064*	.034	-.053	.279	.029	.994	-
Autonomous Motivation → Intention (Total)	.492*	.104	.318	.656	.321	1.000	-
Autonomous Motivation → TPB (Total) → Behavior	.125*	.058	.031	.218	.055	.994	-
Controlled Motivation → Attitude → Behavior	.007	.007	-.024	.083	.006	.926	-
Controlled Motivation → Subjective Norms → Behavior	.013*	.009	-.015	.092	.011	.984	-
Controlled Motivation → PBC → Behavior	.005	.008	-.039	.071	.004	.765	-
Controlled Motivation → Intention (Total)	.103*	.043	.033	.174	.121	.993	-
Controlled Motivation → TPB (Total) → Behavior	.026*	.016	.001	.049	.021	.987	-
Attitude → Behavior	.072*	.043	.005	.139	.043	.985	-
Subjective Norms → Behavior	.037*	.023	.001	.071	.030	.985	-
PBC → Behavior	.353*	.165	.089	.617	.081	.994	-
Past Behavior → Automaticity → Behavior	.056*	.020	.024	.089	.063	.999	-
Past Behavior → Implicit Attitude → Behavior	.004	.009	-.009	.019	.004	.690	-
Past Behavior → SDT → TPB → Behavior	.079*	.034	.026	.136	.089	.994	-
Past Behavior (Total) → Behavior	.548*	.062	.447	.651	.610	1.000	-

Note. Past behavior refers to past free-sugar limiting; Behavior refers to free-sugar limiting behavior. * = MPE indicates a 97.5% likelihood the parameter is in the same direction as the median. logBF = log Bayes Factor.